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# Multivariate and index-based evaluation of long-term reclaimed wastewater quality and reuse suitability

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**ABSTRACT**

**BACKGROUND AND OBJECTIVES:** Reclaimed wastewater is important in water-scarce regions, but safe reuse requires sustained effluent quality. The study objectives were to evaluate the quality and reuse potential of effluent discharged from the Karak domestic wastewater treatment plant in Jordan over the 2016–2025 period. The investigation employed a comprehensive framework integrating regulatory standards, water quality indices, temporal trend evaluations, multivariate statistical techniques, and positive matrix factorization.

**METHODS:** Seventeen physicochemical and microbiological parameters were assessed against Jordanian Standard 893:2021. Water quality index and water pollution index were applied as supplementary screening tools, and parameter-contribution and sensitivity analyses evaluated the magnitude of influence exerted by specific variables and the underlying weighting framework. Linear trends were estimated from 30 campaigns using ordinary least-squares regression, reporting slope, coefficient of determination, and p-value; *Escherichia coli* was evaluated on the log10 scale. Principal component analysis, hierarchical cluster analysis, and Environmental Protection Agency Positive Matrix Factorization 5.0 characterized covariance, similarity, and stable effluent-quality profiles.

**FINDINGS:** Average parameter-level compliance ranged from 50 to 65 percent across reuse and discharge categories, with limitations from residual organic matter, suspended solids, nutrients, bicarbonate, phenol, fats, oils and grease, and *Escherichia coli*. Across all categories, water quality index values surpassed 100. Subsequent sensitivity evaluations revealed that *Escherichia coli* drove approximately 99.99 percent of the weighted index for Class D irrigation and groundwater recharge, whereas phenol dominated Classes B and C. Equal weighting reduced mean Class C water quality index below 100, confirming weighting sensitivity without changing the regulatory compliance conclusion. Water pollution index decomposition also showed dominant *Escherichia coli* influence. Significant decreasing linear trends occurred for biochemical oxygen demand, chemical oxygen demand, total dissolved solids, total suspended solids, total nitrogen, phosphate-phosphorus, chloride, and sodium adsorption ratio, whereas dissolved oxygen, phenol, and nitrate-nitrogen increased. Principal component analysis explained 89.54 percent of variance through four components, and positive matrix factorization resolved four stable profiles contributing 54.0, 20.3, 16.7, and 9.1 percent.

**CONCLUSION:** Index magnitudes were strongly affected by restrictive standards and dominant parameters, while temporal trends indicated directional change without establishing causal treatment mechanisms. Direct Jordanian Standard 893:2021 compliance should remain the primary basis for reuse decisions. Confirming underlying causal mechanisms or targeted treatment interventions necessitates higher-frequency monitoring protocols that encompass influent, hydraulic, operational, and source-specific metrics.

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## INTRODUCTION

Jordan faces severe structural water scarcity driven by limited renewable resources, irregular rainfall, demographic pressure, refugee influxes, climate change, and long-term stress on groundwater and surface-water systems. Renewable freshwater availability has fallen to approximately 61 cubic meters ($m^3$) per capita per year, while rainfall was about 39.5 percent (%) below the long-term average, according to the Ministry of Water and Irrigation (MWI, 2024, 2025b). During 2025, national water allocations relied on groundwater, surface water, and treated wastewater for approximately 58%, 26%, and 16% of demand, respectively. Total utilization reached approximately 1189 million cubic meters (MCM), exceeding the estimated aggregate availability of 1088.25 (MWI, 2025a, 2025b). This persistent deficit increases the strategic importance of reclaimed domestic wastewater. National policy promotes treated wastewater reuse to reduce freshwater demand and support irrigation and industry (Ammary, 2007; Rosas Baños and García Salazar, 2026). Jordan operated 29 wastewater treatment plants in 2025, with about 233 MCM per year design capacity and 214.4 MCM of treated wastewater production (MWI, 2025b). During 2021, approximately 167 of 186 MCM generated was reclaimed and redirected predominantly toward agricultural irrigation in the Jordan Valley subsequent to freshwater blending (MWI, 2023). Effluent reuse serves to substitute freshwater resources, facilitate aquifer recovery, and boost overall resource productivity (Fardous and Al-Hadidi, 2007); furthermore, under controlled quality parameters, wastewater-derived nutrients can substantially lower conventional fertilizer demands (Kalavrouziotis *et al.,* 2023; Ofori *et al.,* 2021). Safe reuse nevertheless depends on sustained effluent quality. Residual organic matter, suspended solids, nutrients, salts, pathogens, and trace contaminants may constrain reuse and threaten soils, crops, surface water, groundwater, and public health (Al-Hazmi *et al.,* 2023; Ukoha-Onuoha and Horsfall, 2026). In Jordan, salinity, chloride, soil properties, sodium adsorption ratio, and crop sensitivity are recognized irrigation constraints (Al-hasanat *et al.,* 2025), and variable treatment performance can undermine compliance with physicochemical and microbiological standards (Ait-Mouheb *et al.,* 2018; Breulmann *et al.,* 2019; Moghaddam *et al.,* 2017). Furthermore, additional pollutant inputs can originate from domestic effluents, unauthorized industrial discharges, stormwater intrusion, septic systems, agricultural return flows, and urban runoff (De Gisi *et al.,* 2017), directly compromising receiving-water quality and the safety of reclaimed water reuse (Dharmadhikari *et al.,* 2023). Integrated monitoring is therefore required to diagnose deterioration and guide wastewater treatment plant (WWTP) management (Nayak and Panda, 2026). Due to the temporal variability inherent in water-quality monitoring metrics, evaluating discrete regulatory parameters in isolation presents significant challenges for environmental synthesis and decision-making (Gupta and Gupta, 2021; Moeinzadeh *et al.,* 2024). Water-quality indices condense multidimensional datasets into standardized scores that streamline classification, comparative evaluation, longitudinal trend analysis, and risk communication (Rana and Ganguly, 2020). Consequently, such frameworks have become central to the assessment of drinking water supplies, irrigation systems, surface waters, groundwater reserves, and wastewater effluents (Abbasi and Abbasi, 2012; Yan *et al.,* 2022; Manna and Biswas, 2023; Patel *et al.,* 2023; Anyango *et al.,* 2024). Wastewater-specific applications include modified wastewater reuse index (WRI) for Jordan (Alfarra *et al.,* 2011), the wastewater polishing index (Verlicchi *et al.,* 2011), and wastewater quality index (WWQI)-based evaluations for agricultural reuse or disposal in Iran, Algeria, Egypt, and Jordan (Jamshidzadeh and Tavangari Barzi , 2020;

Bessedik *et al.,* 2021; Ayoub and El-Morsy, 2021; Alihosseini *et al.,* 2020; Abualhaija, 2023). Index-based assessment can also be strengthened by multivariate and source-apportionment methods, which help identify the processes underlying poor index scores (Chidiac *et al.,* 2023; Kachroud *et al.,* 2019). While extant literature largely emphasizes broad WWQI classification or single-plant assessments, the integration of water quality index (WQI) and water pollution index (WPI) with multivariate statistics and receptor-based source apportionment remains notably scarce. No published study was identified that applies this integrated framework to Karak domestic wastewater treatment plant (DWWTP). The resulting evidence gap is important because reuse decisions in this water-scarce setting require simultaneous evaluation of effluent quality, temporal variability, pollution status, and controlling processes. Combining index-based assessment with multivariate and source-apportionment techniques provides a stronger basis for reuse evaluation, treatment-performance diagnosis, and environmental decision-making. Prior applications of wastewater indices highlight the effectiveness of integrated frameworks in assessing treated effluent quality, determining reuse viability, and monitoring compliance with discharge mandates (Alfarra *et al.,* 2011; Verlicchi *et al.,* 2011; Bessedik *et al.,* 2021; Ayoub and El-Morsy, 2021; Alihosseini *et al.,* 2020). This study aims to evaluate the suitability of effluent from the Karak DWWTP for reliable and sustainable water reuse using an integrated methodological framework. Specifically, the study framework integrates the WQI and WPI for effluent classification;; principal component analysis (PCA) to isolate key variables and latent pollution structures; hierarchical cluster analysis (HCA) to group quality profiles; and positive matrix factorization (PMF) for source apportionment and identification of underlying controlling factors. This study was conducted at the Karak DWWTP, located in Wadi Al-Karak, Karak, Jordan, over a ten-year monitoring during 2016 to 2025.

## MATERIALS AND METHODS

*The study area*

Karak DWWTP is in Wadi Al-Karak, Karak, southern Jordan, about 120 kilometers (km) south of Amman, and serves Karak city and surrounding districts with a total population of about 40,232 according to the Department of Statistics (DOS, 2026). Originally commissioned in 1988 as a trickling-filter system, the facility was retrofitted in 2018 with a mechanical activated-sludge process while maintaining a baseline design capacity of 800 cubic meters per day ($m^3/d$) (MWI, 2023). Actual flows subsequently reached about 1,000–1,200 $m^3/d$, with annual treated discharge estimated at 419,750 cubic meters per year ($m^3/y$) (approximately 1,150 $m^3/d$), indicating hydraulic loading above design capacity (MWI, 2023). Final effluent is discharged to Wadi Al-Karak and supports planned and informal reuse. A 9-km pipeline conveys part of the effluent to the Al-Rasees agricultural project for forest-tree irrigation, while local farmers irrigate lemon, olive, fodder maize, alfalfa, and barley. Approximately 496.48 dunums equivalent to approximately 49.65 hectare (ha) are irrigated under 13 formal agreements reported by MWI (2023). The residual effluent is directed toward the Wadi Al-Karak Dam, which possesses a nominal design storage capacity of approximately 2MCM, subsequently supporting regional irrigation networks and groundwater recharge initiatives (MWI, 2025a). The plant therefore forms an important component of the local non-conventional water-resource system.

*Wastewater sampling and chemical analysis*

Treated domestic wastewater effluent from the Karak DWWTP was monitored over a ten-year period from 2016 to 2025. Samples were collected from the final-effluent discharge point at four-month intervals, translating to three distinct sampling campaigns annually yielding a cumulative total of 30 campaign-level observations. During each campaign, three independent grab samples were obtained from

the WWTP outlet; with the final value for each parameter established as the arithmetic mean of triplicate measurements. The overall precision of the triplicate measurements, expressed as relative standard deviation (RSD), was generally ≤5% for most parameters. Sampling, preservation, transportation and laboratory analysis followed standard methods (Baird *et al.,* 2017). Samples were transported under cooled conditions and stored at 4 degrees Celsius (°C) until analysis. Seventeen physicochemical and microbiological parameters were monitored, including potential of hydrogen (pH), dissolved oxygen (DO), five-day biochemical oxygen demand ($BOD_5$), chemical oxygen demand (COD), total dissolved solids (TDS), total suspended solids (TSS), fats, oils and grease (FOG), methylene blue active substances (MBAS), nitrate-nitrogen ($NO_3$-N), total nitrogen (T-N), phosphate-phosphorus ($PO_4$-P), chloride (Cl), bicarbonate ($HCO_3$), sodium adsorption ratio (SAR), *Escherichia coli* (*E. coli*), and intestinal pathogenic nematode eggs (IPN). The dataset was supplied by Jordan's Ministry of Environment under the National Water Quality Monitoring Project. A summary of the monitored parameters, analytical units, and corresponding analytical methods is presented in Table 1. Due to a temporal resolution constrained to three campaigns annually, the monitoring record is suited for evaluating long-term trends rather than resolving seasonal, short-term hydraulic fluctuations or episodic operational events. The treatment system changed from trickling filters to mechanically operated activated sludge in 2018. Due to limited pre-conversion observations and a lack of matched operational records, temporal patterns observed between 2016–2025 are presented descriptively rather than explicitly linked to the facility modification.

*Calculation of the water quality index*

The WQI was used as a supplementary screening indicator to summarize multi-parameter effluent quality relative to the applicable Jordanian Standard (JS) 893:2021 reuse/discharge category. Within each category, calculations incorporated exclusively those parameters for which JS 893: 2021 mandates an applicable numerical limit or range, while parameters lacking defined limits were excluded from both the category aggregate and its denominator. The Jordanian permissible limits (JS 893:2021) for reclaimed domestic wastewater according to reuse category are presented in Table 2. The WQI was calculated using Eq. 1 (Brown *et al.,* 1972). Because the applied WQI methodology was not specifically developed as a reclaimed-wastewater risk-assessment framework, the resulting index values are interpreted as comparative screening indicators and not as a replacement for direct regulatory compliance assessment.

$$QI = \sum_{i=1}^{n} \frac{Wi \times Qi}{\sum_{i=1}^{n} Wi} \quad (1)$$

Where: Wi denotes the unit weight of the $i^{th}$ parameter, Qi denotes the water quality rating of the $i^{th}$ parameter, and (n) denotes the number of the involved parameters in the calculation. The water quality rating (Qi) was calculated, using Eq. 2 (Brown *et al.,* 1972):

$$Qi = 100 \times \left[\frac{(Vi - Vid)}{(Si - Vid)}\right] \quad (2)$$

Where: Vi is the measured value of the $i^{th}$ parameter, Vid is the reference or ideal value used in the WQI calculation, and Si is the applicable JS 893:2021 limit for the intended use. In the calculations that generated the reported WQI series, Vid was 0 for non-pH parameters and 7.5 for pH. Because this methodological convention lacks wastewater-specific calibration, posing interpretive challenges for parameters such as dissolved oxygen; therefore, WQI magnitude is evaluated conservatively, absolute index values are decoupled from health-risk implications, and direct parameter-by-parameter compliance remains the primary reuse criterion for water reuse. Wi is inversely proportional to Si, using Eq. 3 (Brown *et al.,* 1972):

Table 1: Monitored parameters, analytical units, and corresponding analytical methods

| Parameter | Unit | Reference method (Ayres *et al.,* 1996; HACH, 2006; Baird *et al.,* 2017) | Method |
|---|---|---|---|
| pH | Standard units (SU) | SM 4500-$H^+$ B, 2017 | Electrometric method |
| DO | Milligram per liter (mg/L) | HACH Method 10360 (HACH, 2006) | Luminescence measurement of dissolved oxygen (LDO) in water and wastewater |
| $BOD_5$ | mg/L | SM 5210-B, 2017 | 5-day biochemical oxygen demand test |
| COD | mg/L | SM 5220-B, 2017 | Open reflux method |
| TDS | mg/L | SM 2540-C, 2017 | Total dissolved solids dried at 180 °C |
| TSS | mg/L | SM 2540-D, 2017 | Total suspended solids dried at 103–105°C |
| FOG | mg/L | SM 5520-B, 2017 | Liquid-Liquid, Partition- Gravimetric Method |
| Phenol | mg/L | SM 5530-C, 2017 | Chloroform extraction method |
| MBAS | mg/L | SM 5540-C, 2017 | Anionic surfactants as MBAS |
| $NO_3$ – N | mg/L | SM 4110-B, 2017 | Ion chromatography with chemical suppression of eluent conductivity |
| T-N | mg/L | Calculation | - |
| PO4-P | mg/L | SM 4500-P, C, 2017 | Vanadomolybdophosphoric acid colorimetric method |
| Cl | mg/L | SM 4500-Cl, D, 2017 | Potentiometric method |
| HCO3 | mg/L | SM 2320-B, 2017 | Titration method |
| SAR | Unitless | Calculation | - |
| *E. coli* | Most probable number (MPN) 100/mL | SM 9221-F, 2017 | *Escherichia coli* procedure using fluorogenic substrate |
| IPN | Eggs/L | Modified Bailenger Method, World Health Organization (WHO) report 1996 | Modified Bailenger Method |

$$Wi = \frac{K}{Si} \quad (3)$$

Where: K is the constant of proportionality and is computed, using Eq. 4 (Brown *et al.,* 1972):

$$\mathrm{K} = \frac{1}{\sum \frac{1}{\mathrm{Si}}} \quad (4)$$

Water quality is classified into five categories based on WQI values: Excellent water quality (WQI value 0- 25), Good water quality (WQI value 26-50), Poor water quality (WQI value 51-75), Very poor water quality (WQI value 76-100), Unsuitable for the intended use (WQI value >100), where the lower the WQI value, the better the water quality, and the higher the WQI value, the poorer the water (Brown *et al.,* 1972; Tyagi *et al.,* 2013; Kachroud *et al.,* 2019).

*Calculation of the water pollution index*

Additionally, the WPI served as a supplementary screening tool, standardizing observed concentrations against applicable regulatory thresholds and aggregating the resulting pollution loads free of subjective weights (Hossain and Patra, 2020; Syeed *et al.,* 2023). As for WQI, each reuse/discharge category used only parameters with an applicable JS 893:2021 limit; non-applicable parameters were omitted from that category-specific calculation and denominator, as documented in Table 2. The WPI was calculated using Eq. 5 (Hossain and Patra, 2020). Regulatory compliance with individual critical parameters, particularly microbiological limits, served as the primary decision criterion, as composite index scores can obscure the disparate environmental and public health consequences of different exceedances across healthcare facilities and geographic regions under varying regulatory conditions.

$$\mathrm{WPI} = \frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{PLi} \quad (5)$$

Where: Pli is the pollution load of the $i^{th}$ parameter; (n) represents the number of all parameters. The calculation of the pollution load (PLi) was performed using Eq. 6 (Hossain and Patra, 2020):

Table 2: Jordanian permissible limits (JS 893:2021) for reclaimed domestic wastewater according to reuse category

| Parameter | Unit | artificial recharge of groundwater aquifers | discharge into streams, wadies and water bodies | Irrigation reuse-Class A | Irrigation reuse-Class B | Irrigation reuse-Class C | Irrigation reuse-Class D |
|---|---|---|---|---|---|---|---|
| pH | SU | 6-9 | 6-9 | 6-9 | 6-9 | 6-9 | 1 or…6-9 |
| DO | mg/L | >2 | >1 | >2 | - | - | >2 |
| $BOD_5$ | mg/L | 15 | 60 | 30 | 100 | 200 | 15 |
| COD | mg/L | 50 | 150 | 100 | 200 | 300 | 50 |
| TDS | mg/L | 1500 | 1500 | 1500 | 1500 | 1500 | 1500 |
| TSS | mg/L | 50 | 60 | 50 | 100 | 100 | 15 |
| FOG | mg/L | 8 | 8 | 8 | 8 | 8 | 2 |
| Phenol | mg/L | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 |
| MBAS | mg/L | 25 | 25 | 100 | 100 | 100 | 15 |
| $NO_3$-N | mg/L | 7 | 20 | 16 | 16 | 16 | 16 |
| T-N | mg/L | 20 | 70 | 70 | 70 | 70 | 70 |
| $PO_4$-P | mg/L | 5 | 5 | 10 | 10 | 10 | 10 |
| Cl | mg/L | 350 | 500 | 500 | 500 | 500 | 500 |
| $HCO_3$ | mg/L | 400 | 400 | 400 | 400 | 400 | 400 |
| SAR | Unitless | 6 | 6 | 9 | 9 | 9 | 9 |
| *E. coli* | MPN 100/mL | 1.1 | 1000 | 100 | 1000 | - | 1.1 |
| IPN | Eggs/L | ≤1 | ≤1 | ≤1 | ≤1 | ≤1 | ≤1 |

Note: "-'' indicates that no permissible limit was specified
pH is checked within range; DO is checked as a minimum; other numeric parameters are checked as maximum limits
Class A: parks, playgrounds, and sides of roads inside the cities
Class B: fruit trees, sides of roads outside the cities, and green areas
Class C: field crops, industrial crops, and forest trees
Class D: cut flowers

$$PLi = 1 + \left(\frac{Ci - Si}{Si}\right) \quad (6)$$

Where: Ci is the laboratory-analyzed concentration of the $i^{th}$ parameter, Si denotes each Jordanian parameter's standard or maximum acceptable limit. The calculation of PLi for the pH parameter is based on the pH value, using Eqs. 7 and 8 (Hossain and Patra, 2020):

$$\mathrm{PLi} = \frac{\mathrm{Ci\text{-}7}}{\mathrm{Sia\text{-}7}} \text{ , If the pH < 7} \quad (7)$$

$$\mathrm{PLi} = \frac{\mathrm{Ci\text{-}7}}{\mathrm{Sib\text{-}7}} \text{ , If the pH > 7} \quad (8)$$

Where: $Si_a$ denotes the lowest permissible pH value for the intended use, $Si_b$ denotes the highest allowable pH value for the intended use.

The classifications of water quality based on WPI results are divided into four categories: excellent water quality (WPI value < 0.5), good water quality (WPI value 0.5-0.75), moderately polluted water (WPI value 0.75-1), and highly polluted water (WPI value >1) (Hossain and Patra, 2020). Parameter-contribution and sensitivity analyses were executed utilizing the identical annual category-specific standards and parameter configurations applied for the reported indices. For WQI, parameter leverage was quantified as the fixed weighted-term contribution, 100(WiQi)/Σ(WjQj), aggregated over the 2016–2025 annual calculations. A leave-one-parameter-out calculation was used for selected dominant terms, with K renormalized after omission, and an equal-weight WQI (arithmetic mean of Qi across applicable parameters) was calculated to test dependence on the inverse-standard weighting scheme. For WPI, individual parameter contributions were determined as 100PLi/ΣPLj, and WPI was subsequently re-evaluated excluding *E. coli* instances where applicable standard applied. These sensitivity calculations quantify mathematical leverage within the indices and are not interpreted as causal pollutant-source apportionment. Ordinary least-squares regression was applied to evaluate linear temporal trends spanning 2016–2025, utilizing the 30

campaign-level observations across each of the 16 quantitative parameters retained within the multivariate dataset. Time was represented as decimal year according to the actual routine sampling months (January = year, May = year + 4/12, and September = year + 8/12), so the regression slope represents the average change per year. For each parameter, the slope, coefficient of determination ($R^2$), and two-sided p-value for the slope were reported. *E. coli* was analyzed on the base-10 logarithmic ($log_{10}$) scale because of its several-order-of-magnitude range; all other parameters were analyzed on their measured scales. The regressions quantify monotonic temporal association across the entire record rather than serving as indicators of seasonal dynamics, intervention outcomes, or causal treatment-process responses. Because 16 parallel regressions were evaluated, nominal p-values are presented transparently and interpreted strictly as exploratory evidence.

*Multivariate statistical analysis*

*Principal component analysis*

PCA was applied to the 30 campaign-level observations and 16 variables retained after exclusion of IPN (pH, DO, $BOD_5$(f), COD, TDS, TSS, FOG, phenol, MBAS, $NO_3$–N, T-N, $PO_4$–P, $Cl^-$, $HCO_3^-$, SAR and *E. coli*). Variables were standardized and PCA was performed on the correlation matrix. The Kaiser-Meyer-Olkin (KMO) value was 0.82 and Bartlett's test was significant ($\chi^2 = 1052.18$, degrees of freedom (df) = 120, $p < 0.001$), indicating that the observed correlation structure was suitable for dimension reduction; these tests do not, however, remove the limitation of the low observation-to-variable ratio (30:16). Consequently, PCA is applied as an exploratory pattern recognition technique rather than as a definitive or broadly generalizable latent-process model. Components with eigenvalues >1 were retained and varimax rotation was used to aid interpretation. Seasonal, causal, and pre- or post-upgrade inferences were intentionally excluded from the PCA interpretation, as data were restricted to three annual campaigns and lacked paired process or operational available. Analyses were conducted using International Business Machines (IBM) Statistical Package for the Social Sciences (SPSS) Statistics version 26.

*Hierarchical cluster analysis*

HCA was used as a complementary description of similarity among the same 16 standardized effluent-quality variables. Agglomerative hierarchical clustering was performed using squared Euclidean distance and Ward's minimum-variance linkage, with the resulting dendrogram evaluated for coherent variable groupings. Because HCA and PCA were derived from the same 30 × 16 dataset, HCA is not construed as an independent validation of PCA nor as conclusive evidence of causal pollutant sources. Its added value is descriptive, illustrating which variables merge at shorter linkage distances and indicating whether covariance groupings align broadly consistent with the PCA structure. Note that IPN was excluded due to its non-detection across all analyzed samples.

*Positive matrix factorization*

PMF was applied as an exploratory receptor-model analysis to resolve non-negative statistical factor profiles in the final-effluent dataset. U.S. Environmental Protection Agency (EPA) PMF 5.0 decomposes the observed concentration matrix into factor-contribution and factor-profile matrices while weighting observations by uncertainty (Paatero and Tapper, 1994; Norris *et al.,* 2014). The input matrix incorporated the identical 16 final-effluent variables utilized in the multivariate analyses; with IPN excluded due to its non-detection across the samples. Importantly, the analysis did not include influent concentrations, source fingerprints, process-unit samples, hydraulic/operational records, rainfall, sludge characteristics or disinfection data. Consequently, the extracted factors are interpreted strictly as statistical profiles or potential process-associated patterns rather than

verified external pollutant sources or established treatment mechanisms. The measured matrix X was decomposed into G and F under non-negativity constraints using Eq. 9 (Norris *et al.,* 2014).

$$\chi_{ij} = \sum_{k=1}^{P} g_{ik} f_{kj} + e_{ij} \quad (9)$$

Where: $x_{ij}$ is the measured concentration of variable j in sample i, $g_{ik}$ is the contribution of factor k, $f_{kj}$ is the factor profile, $e_{ij}$ is the residual, and p is the number of resolved factors. The optimal solution was obtained by minimizing the uncertainty-weighted objective function, using Eq. 10 (Norris *et al.,* 2014):

$$Q = \sum_{i=1}^{n} \sum_{j=1}^{m} \left(\frac{e_{ij}}{u_{ij}}\right)^2 \quad (10)$$

Where: $u_{ij}$ represents the observation-specific uncertainty. Uncertainties were calculated following the EPA PMF 5.0 equation-based approach: values at or below the method detection limit (MDL) were assigned $u_{ij}$ =5/6×MDLj, whereas values above the MDL were assigned, using Eq. 11 (Norris *et al.,* 2014):

$$u_{ij} = \sqrt{\left(EF_j x_{ij}\right)^2 + \left(0.5 MDL_j\right)^2} \quad (11)$$

Where: EFj is the species-specific error fraction. The PMF input contained 30 observations for each of the 16 modeled variables and no missing values. Species-specific MDLs and error fractions were used in the uncertainty calculation. Based on the signal-to-noise assessment, 13 variables were classified as strong, while FOG, $NO_3$-N and *E. coli* were classified as weak and down-weighted by tripling their uncertainties. These preprocessing choices defined the uncertainty structure used to weigh the PMF input matrix. The relative contribution of each factor to each variable was calculated using Eq. 12, while the corresponding factor contribution was determined using Eq. 13.

$$C_{kj} = \sum_{i=1}^{n} g_{ik} f_{kj} \quad (12)$$

$$RC_{kj} = \frac{C_{kj}}{\sum_{k=1}^{p} C_{kj}} \times 100 \quad (13)$$

Where: $RC_{kj}$ is the relative contribution of factor k to variable j. Candidate PMF solutions were evaluated through a comprehensive suite of diagnostics, including convergence criteria, Q statistics, scaled residuals, observed-predicted agreement, species-specific Q/Qexpected ratios, interpretability, bootstrap mapping, displacement (DISP) and bootstrap-displacement (BS-DISP) analyses. Three-, four- and five-factor solutions were examined; the four-factor solution was selected because it provided the best balance between numerical fit, factor separation and interpretability. For the selected solution, all 100 base runs converged; Q(true), Q(robust) and Q(expected) were 244.495, 228.335 and 218, respectively, giving Q(robust)/Q(expected)=1.047. A total of 98.54% of scaled residuals were within +/-3, all species-specific Q/Qexpected values were below 2, and bootstrap mapping to the corresponding base factors ranged from 93% to 98%. DISP and BS-DISP showed no factor swaps, supporting limited rotational ambiguity. While these diagnostics confirm the internal numerical stability of the selected solution, they do not independently validate the environmental or causal identity of the factors. Accordingly, the extracted factors represent descriptive statistical groupings or prospective process patterns, requiring supplementary operational or source verification to establish causal links. Although the diagnostics collectively validate the mathematical stability of the four-factor model, environmental interpretation is inherently constrained by the limits of the available final-effluent evidence. Therefore, the relative contributions of each variable across all PMF factors sum to 100%. The average contribution of each PMF factor to the overall source/process apportionment was calculated, using Eq. 14 (Paatero and Tapper, 1994; Brown *et al.,* 2015):

$$AFC_k = \frac{\sum_{j=1}^{m} C_{kj}}{\sum_{k=1}^{p}\sum_{j=1}^{m} C_{kj}} \times 100 \quad (14)$$

Where: $AFC_k$ is the average contribution of factor k. Accordingly, factor-profile bar charts were used to visualize the relative contributions of the studied variables to the resolved PMF factors, while the factor-contribution pie chart summarized the average contribution of each factor to the total apportioned effluent-quality matrix. The PMF results were interpreted as source and process apportionment, relying on the proportional share of each variable assigned to every respective factor profile alongside the average factor contributions.

*Descriptive statistics*

Descriptive statistics were performed for each measured effluent parameter to summarize the central tendency, variability, and distribution of the WWTP dataset. The statistical descriptors included the mean, standard deviation (SD), median (Q2), minimum, maximum, coefficient of variation (CV), first quartile (Q1), and third quartile (Q3). These analyses were performed utilizing SPSS Statistics (version 26) to establish a preliminary characterization of the effluent quality dataset and to lay the groundwork for subsequent multivariate analysis.

*Quality assurance and quality control*

All analyses were performed at the Royal Scientific Society laboratories under International Organization for Standardization/International Electrotechnical Commission (ISO/IEC) 17025 accreditation. Quality assurance (QA) and quality control (QC) procedures followed ISO/IEC 17025:2017 and accredited methods to ensure data traceability, precision, and accuracy. Each analytical batch incorporated calibration verification, procedural blanks, control standards, and duplicate analyses where applicable, whereas analytical accuracy and matrix effects were evaluated using certified reference materials and/or matrix-spike recoveries. Analytical results were validated against method-specific criteria, including calibration linearity, blank response, spike recovery, and relative percentage difference, with corrective action and reanalysis executed upon non-compliance to ensure that exclusively quality-assured data were integrated into the final report.

## RESULTS AND DISCUSSION

*Effluent characterization and compliance assessment*

The ten-year final-effluent record (Table 3) shows partial compliance with JS 893:2021. pH was within the permissible range across categories, while DO, TDS, MBAS, SAR and IPN eggs showed full or near-full compliance where standards were applicable. Chloride concentrations satisfied regulatory thresholds established for irrigation and surface-discharge; however, they exceeded acceptable constraints for artificial groundwater recharge applications. The most frequent limitations involved $BOD_5$, COD and TSS, together with T-N, $PO_4$-P, $HCO_3^-$, phenol and *E. coli*. While these patterns align with inadequate regulation of residual organics, suspended solids, nutrients, alkalinity and microbiological parameters, the final-effluent dataset alone is insufficient to determine whether individual exceedances stem from influent fluctuations, hydraulic variations, operational dynamics, disinfection efficiencies, or extraneous factors. *E. coli* exceedances are therefore described as evidence of insufficient final microbial quality relative to the standard rather than proof of a specific disinfection failure. Instances of $HCO_3^-$ non-compliance manifested despite complete compliance with TDS/SAR standards, demonstrating that alkalinity-related irrigation limitations can emerge independently of overall salinity/sodicity conditions. The 50–65% average parameter-level compliance is an unweighted descriptive summary and does not account for differences in the environmental or public-health significance of individual exceedances. Uncompromising adherence to each

Table 3: Descriptive statistics and compliance summary of the final effluent quality for Karak DWWTP over the ten years (2016 -2025) monitoring period

| Parameter | Mean ±SD | Median | Min-Max | Q1 | Q3 | CV (%) | Compliance percentage against each Jordanian reclaimed wastewater reuse standard category JS 893:2021 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Irrigation reuse-Class A | Irrigation reuse- Class B | Irrigation reuse-Class C | Irrigation reuse-Class D | Discharge into streams, wadies and water bodies | Artificial groundwater recharge |
| pH | 7.68 ± 0.15 | 7.69 | 7.30-7.93 | 7.60 | 7.80 | 2 | 100% | 100% | 100% | 100% | 100% | 100% |
| DO | 5.78 ± 1.11 | 5.71 | 3.85-8.00 | 4.94 | 6.54 | 19 | 100% | N/A | N/A | 100% | 100% | 100% |
| BOD5 | 104.45 ± 85.55 | 70.25 | 11.70-286.00 | 37.39 | 140.00 | 82 | 10% | 57% | 83% | 3% | 43% | 3% |
| COD | 399.96 ± 267.75 | 501.00 | 60.80-840.00 | 132.93 | 573.25 | 67 | 20% | 40% | 43% | 0% | 33% | 0% |
| TDS | 1105.50 ± 135.77 | 1120.00 | 880.00-1280.00 | 970.00 | 1231.25 | 12 | 100% | 100% | 100% | 100% | 100% | 100% |
| TSS | 213.59 ± 138.10 | 277.50 | 24.00-430.00 | 60.25 | 317.50 | 65 | 17% | 37% | 37% | 0% | 23% | 17% |
| FOG | 8.72 ± 1.31 | 8.00 | 8.00-12.90 | 8.00 | 8.85 | 15 | 57% | 57% | 57% | 0% | 57% | 57% |
| Phenol | 0.03 ± 0.01 | 0.02 | 0.02-0.04 | 0.02 | 0.03 | 29 | 17% | 17% | 17% | 17% | 17% | 17% |
| MBAS | 1.24 ± 0.62 | 1.52 | 0.15-1.80 | 0.74 | 1.69 | 50 | 100% | 100% | 100% | 100% | 100% | 100% |
| NO3-N | 4.34 ± 7.71 | 1.00 | 0.23-29.90 | 0.88 | 3.48 | 178 | 93% | 93% | 93% | 93% | 93% | 80% |
| T-N | 95.60 ± 33.03 | 100.12 | 31.40-199.24 | 83.03 | 112.56 | 35 | 20% | 20% | 20% | 20% | 20% | 0% |
| PO4-P | 16.47 ± 8.07 | 19.35 | 0.73-24.20 | 13.65 | 22.80 | 49 | 20% | 20% | 20% | 20% | 20% | 20% |
| Cl | 322.50 ± 42.23 | 327.00 | 261.00-378.00 | 283.00 | 362.25 | 13 | 100% | 100% | 100% | 100% | 100% | 50% |
| HCO3 | 701.53 ± 124.31 | 725.00 | 449.00-850.00 | 708.75 | 768.00 | 18 | 0% | 0% | 0% | 0% | 0% | 0% |
| SAR | 4.92 ± 0.51 | 5.00 | 3.94-5.55 | 4.64 | 5.35 | 10 | 100% | 100% | 100% | 100% | 100% | 100% |
| *E. coli* | 7.37E+05 ± 5.61E+05 | 5.77E+05 | 3.30E+02-1.8E+06 | 2.97E+05 | 1.02E+06 | 140 | 0% | 3% | N/A | 0% | 3% | 0% |
| IPN | - | - | - | - | - | - | 100% | 100% | 100% | 100% | 100% | 100% |
| Average of parameter-level compliance percentages | | | | | | | 56% | 59% | 65% | 50% | 59% | 50% |
| Main restriction (parameter(s) that limit each intended use according to Jordanian standards) | | | | | | | $HCO_3^-$, *E. coli*, $BOD_5$, COD, TSS, Phenol, T-N, $PO_4$-P | $HCO_3^-$, *E. coli*, Phenol, T-N, $PO_4$-P, TSS, COD | $HCO_3^-$, Phenol, T-N, $PO_4$-P, TSS, COD | COD, TSS, FOG, $HCO_3^-$, *E. coli*, $BOD_5$, Phenol, T-N, $PO_4$-P | $HCO_3^-$, *E.coli*, Phenol, T-N, $PO_4$-P, TSS, COD, $BOD_5$ | COD, T-N, $HCO_3^-$, *E. coli*, $BOD_5$, TSS, Phenol, $PO_4$-P, $Cl^-$ |

Note: Class A: parks, playgrounds, and sides of roads inside the cities. Class B: fruit trees, sides of roads outside the cities, and green areas. Class C: field crops, industrial crops, and forest trees. Class D: cut flowers. The arithmetic mean was calculated for all tests except for Escherichia coli, for which the geometric mean was calculated. n = 30 sampling campaigns (3 campaigns per year over 2016–2025). Mean ± SD was calculated from campaign-level mean values over the 2016–2025 monitoring period. -: Not detected (0 eggs/L). Parameters not mentioned in the Jordanian reclaimed wastewater reuse standard category JS 893 were not included in compliance calculations; Compliance percentage= (number samples meeting the applicable Jordanian reuse/discharge standard ÷ total numeric samples) × 100. N/A: Not applicable because no standard available.

applicable JS 893:2021 limit continues to serve as the foundational criterion for operational management decisions.

*WQI based reclaimed wastewater assessment*

All annual WQI values exceeded 100 (Table 4), but the parameter-contribution analysis showed that the index was strongly concentrated in a small number of weighted terms (Table 5). Across 2016–2025, phenol accounted for 52.02% of the Class A weighted WQI term and 98.42% and 99.31% of Classes B and C, respectively, whereas *E. coli* accounted for 99.985% of Class D and 99.986% of artificial-recharge WQI. For Class A, *E. coli* accounted for an additional 46.27%. Consequently, the pronounced magnitudes observed in Class D and artificial recharge assessments stem primarily from the interplay between elevated *E. coli* concentrations and the highly rigorous 1.1 MPN/100 mL criterion, rather than from uniformly extreme deterioration in all measured variables. Excluding *E. coli* and renormalizing the WQI reduced the 2016–2025 mean from 878,860.47 to 132.04 for Class D and from 881,753.08 to 128.58 for artificial recharge; both remained above 100. Class A similarly decreased from 236.07 to 126.87. Conversely, excluding phenol decreased the mean WQI to 65.74 for Class B and 28.66 for Class C, illustrating that the numerical classification of both categories is particularly vulnerable to the stringent phenol threshold and the inverse-standard weighting configuration. The annual WQI pattern was lower in 2021–2022 and higher again in 2024–2025 (Table 4). This finding is documented exclusively as a descriptive temporal pattern only. A weighting-scheme sensitivity test using equal parameter weights changed the 2016–2025 mean Class C WQI from 125.00 to 89.74, whereas the other five reuse/discharge categories remained above 100. Thus, the absolute WQI magnitude and, for Class C, even the screening class are sensitive to weighting assumptions. This sensitivity does not alter the overarching management conclusion, given that direct parameter-specific compliance with JS 893:2021 remains the primary criterion and Class C continues to exhibit recurring regulatory exceedances. The dataset cannot definitively attribute interannual variation to hydraulic loading, influent composition, process control, disinfection efficacy, or the 2018 plant conversion because operational data are unavailable and sampling was limited to three annual campaigns.

*WPI based reclaimed wastewater assessment*

WPI similarly indicated limited reuse suitability, but its message differed from WQI for Class C irrigation. Class C had the lowest WPI values and averaged 0.91, whereas WQI remained >100 and individual parameters still failed applicable standards (Table 6). Accordingly, WPI is not interpreted as evidence that Class C reuse is compliant or generally feasible. Class C is described only as the least impaired category in the WPI screening, while direct JS 893:2021 compliance, especially microbiological and other critical limits, remains the controlling decision criterion. The WPI parameter decomposition established that *E. coli* serves as the primary mathematical contributor across all categories governed by microbiological standard (Table 7). *E. coli* accounted for 99.57% of mean Class A WPI, 97.45% of Class B, 95.74% of discharge, 99.991% of Class D and 99.993% of artificial-recharge WPI. Class C, for which no *E. coli* limit is specified in the applied category, showed a distributed WPI structure led by TSS (15.61%), HCO3 (12.82%), PO4-P (12.04%), T-N (9.98%), COD (9.75%) and phenol (9.36%). Excluding *E. coli* and recalculating WPI reduced the mean values to 1.52 for Class A, 0.99 for Class B, 1.58 for discharge, 2.82 for Class D and 2.36 for artificial recharge. Consequently, *E. coli* drives the exceptionally high WPI in stricter categories, while substantial physicochemical pollution persists, particularly in Class D and artificial recharge applications. Thus, the Class C mean WPI of 0. 91 should be interpreted as a screening metric rather than definitive regulatory compliance.

Table 4: annual values of WQI for the effluent of Karak DWWTP during 2016–2025

| Year | Irrigation reuse-Class A | Irrigation reuse-Class B | Irrigation reuse-Class C | Irrigation reuse-Class D | Discharge into streams and wadies or water bodies | Artificial recharge of groundwater aquifers |
|---|---|---|---|---|---|---|
| 2016 | 302 | 110 | 108 | 1543915 | 118 | 1548998 |
| 2017 | 291 | 105 | 103 | 1497596 | 114 | 1502526 |
| 2018 | 287 | 106 | 104 | 1451283 | 116 | 1456061 |
| 2019 | 284 | 109 | 108 | 1404972 | 119 | 1409598 |
| 2020 | 288 | 109 | 108 | 1435848 | 120 | 1440576 |
| 2021 | 135 | 103 | 103 | 247115 | 112 | 247926 |
| 2022 | 129 | 114 | 114 | 103552 | 126 | 103890 |
| 2023 | 178 | 116 | 115 | 494134 | 124 | 495759 |
| 2024 | 234 | 195 | 195 | 308956 | 203 | 309971 |
| 2025 | 232 | 194 | 193 | 301235 | 202 | 302225 |
| Average 2016-2025 | 236 | 126 | 125 | 878860 | 135 | 881753 |

Notes: Class A: parks, playgrounds, and sides of roads inside the cities. Class B: fruit trees, sides of roads outside the cities, and green areas. Class C: field crops, industrial crops, and forest trees. Class D: cut flowers. Lower WQI values reveal better effluent quality and compliance with the relevant standards, while higher values reveal poorer water quality.

Table 5: Parameter-contribution and targeted sensitivity analysis of mean WQI (2016–2025)

| Category | Mean WQI | Dominant weighted-term contribution | Targeted sensitivity |
|---|---|---|---|
| Class A | 236.07 | Phenol 52.02%; *E. coli* 46.27%; DO 1.17% | Without *E. coli*: 126.87 (>100) |
| Class B | 126.11 | Phenol 98.42%; *E. coli* 0.88%; PO4-P 0.25% | Without phenol: 65.74 |
| Class C | 125.00 | Phenol 99.31%; PO4-P 0.26%; FOG 0.21% | Without phenol: 28.66 |
| Class D | 878,860.47 | *E. coli* 99.985%; phenol 0.014% | Without *E. coli*: 132.04 (>100) |
| Discharge | 135.41 | Phenol 89.59%; DO 8.09%; PO4-P 0.92% | Equal-weight sensitivity assessed in text |
| Artificial recharge | 881,753.08 | *E. coli* 99.986%; phenol 0.014% | Without *E. coli*: 128.58 (>100) |

Note: Contributions are mathematical shares of the weighted WQI terms, not environmental-risk shares. Leave-one-parameter-out values were recalculated with K renormalized after omission.

Table 6: Annual values WPI for the effluent of Karak DWWTP during 2016–2025, evaluated against Jordanian standards (JS 893:2021) for reclaimed domestic wastewater according to reuse purposes (JSMO, 2021)

| Year | Irrigation reuse- Class A | Irrigation reuse- Class B | Irrigation reuse-Class C | Irrigation reuse- Class D | Discharge into streams and wadies or water bodies | Artificial recharge of groundwater aquifers |
|---|---|---|---|---|---|---|
| 2016 | 590 | 64 | 1.16 | 53480 | 61 | 53479 |
| 2017 | 572 | 62 | 1.12 | 51875 | 59 | 51875 |
| 2018 | 555 | 60 | 1.10 | 50271 | 57 | 50270 |
| 2019 | 537 | 58 | 1.08 | 48667 | 55 | 48666 |
| 2020 | 549 | 59 | 1.06 | 49736 | 56 | 49735 |
| 2021 | 95 | 11 | 0.74 | 8558 | 11 | 8558 |
| 2022 | 40 | 5 | 0.57 | 3584 | 5 | 3584 |
| 2023 | 189 | 21 | 0.52 | 17113 | 20 | 17113 |
| 2024 | 119 | 13 | 0.89 | 10697 | 13 | 10697 |
| 2025 | 116 | 13 | 0.89 | 10430 | 13 | 10430 |
| Average 2016-2025 | 336 | 37 | 0.91 | 30441 | 35 | 30441 |

Notes: Class A: parks, playgrounds, and sides of roads inside the cities. Class B: fruit trees, sides of roads outside the cities, and green areas. Class C: field crops, industrial crops, and forest trees. Class D: cut flowers. Lower WPI values reveal compliance with the relevant standards; whereas higher values reveal greater pollution

Table 7: Parameter contributions and *E. coli*-exclusion sensitivity of mean WPI (2016–2025)

| Category | Mean WPI | Dominant WPI contribution | WPI without *E. coli* |
|---|---|---|---|
| Class A | 336.25 | *E. coli* 99.57%; TSS 0.08%; COD 0.07% | 1.52 |
| Class B | 36.50 | *E. coli* 97.45%; TSS 0.37%; COD 0.34% | 0.99 |
| Class C | 0.912 | TSS 15.61%; HCO3 12.82%; PO4-P 12.04%; T-N 9.98% | N/A (no *E. coli* standard) |
| Class D | 30,441.16 | *E. coli* 99.991%; TSS 0.003%; COD 0.002% | 2.82 |
| Discharge | 34.97 | *E. coli* 95.74%; DO 0.97%; TSS 0.60% | 1.58 |
| Artificial recharge | 30,440.73 | *E. coli* 99.993%; COD 0.002%; BOD5 0.001% | 2.36 |

Note: WPI contribution (%) = 100PLi/ΣPLj, aggregated across the annual calculations. *E. coli*-exclusion WPI was recalculated with the number of included parameters reduced accordingly.

*Linear temporal trend analysis (2016–2025)*

Regression across the 30 campaign observations identified several systematic long-term changes in final-effluent quality (Table 8). Significant decreasing slopes (nominal $p < 0.05$) were observed for $BOD_5$ (−10.844 mg/L/y), COD (−60.290 mg/L/y), TDS (−39.861 mg/L/y), TSS (−33.637 mg/L/y), T-N (−5.089 mg/L/y), $PO_4$-P (−1.726 mg/L/y), Cl (−11.675 mg/L/y), and SAR (−0.117 units/y). DO increased significantly (+0.170 mg/L/year), while phenol (+0.00187 mg/L/y) and $NO_3$-N (+1.483 mg/L/y) also showed significant upward trends. The strongest linear temporal fits were observed for TDS ($R^2 = 0.742$), Cl ($R^2 = 0.658$), phenol ($R^2 = 0.545$), TSS ($R^2 = 0.511$), and SAR ($R^2 = 0.456$). Trends in pH, FOG, MBAS and $HCO_3$ were not statistically significant, and the log10 *E. coli* slope was negative but marginal (−0.0923 log10 MPN/100 mL/y; $R^2 = 0.130$; $p = 0.0508$). These outcomes illustrate interannual directionality within the monitored timeline; however, they neither resolve seasonal cycles nor confirm that the 2018 treatment conversion or unmeasured operational variables drove the observed temporal shifts.

*PCA-based identification of water quality drivers*

The four retained varimax-rotated PCA components explained 89.54% of the variance (Table 9). Given the 30:16 observation-to-variable ratio, the PCA is interpreted as exploratory covariance structure. principal component 1 (PC1; 46.25%) was characterized mainly by $BOD_5$(f), COD, TSS, TDS, $PO_4$-P, Cl and SAR, describing a broad residual organic/solids/salinity covariance domain. These co-loadings indicate that the variables exhibited synchronous variations within the monitored final effluent; however, they cannot independently isolate a common source or substantiate a specific treatment mechanism. Comparable variable groupings have been reported in wastewater multivariate studies (Pantsar-Kallio *et al.,* 1999; Singh *et al.,* 2005; Kumari and Tripathi, 2014). Bold number: loading value ≥ 0.60, indicating heavy loading. PC2 (15.79%) was characterized by pH, FOG and T-N; PC3 (15.25%) by phenol, MBAS, $NO_3$-N and $HCO_3$; and PC4 (12.25%) mainly by DO and *E. coli* (Table 8). These components are described as statistical associations: a pH–FOG–T-N pattern, a phenol–MBAS–$NO_3$-N–$HCO_3$ pattern, and a DO–*E. coli* pattern. Although biological or operational mechanisms, including nitrogen transformation, aeration, sedimentation, disinfection, and detergent-derived inputs, serve as plausible hypotheses, they cannot be definitively confirmed through final-effluent covariance análisis alone. The absence of influent, process-unit, operational and source-profile data prevents causal attribution. Accordingly, these components are interpreted as statistical associations and patterns rather than definitive process drivers or source signatures and should therefore be considered hypotheses requiring independent operational and source-specific verification through targeted investigations.

Table 8: Linear temporal trends in final-effluent quality parameters across 30 monitoring campaigns, 2016–2025

| Parameter | Slope | $R^2$ | p-value | Direction |
|---|---|---|---|---|
| pH | +0.00906 SU/y | 0.031 | 0.3521 | No significant trend |
| DO | +0.170 mg/L/y | 0.204 | 0.0122 | Increase |
| $BOD_5$ | −10.844 mg/L/y | 0.138 | 0.0430 | Decrease |
| COD | −60.290 mg/L/y | 0.437 | $7.06 \times 10^{-5}$ | Decrease |
| TDS | −39.861 mg/L/y | 0.742 | $9.80 \times 10^{-10}$ | Decrease |
| TSS | −33.637 mg/L/y | 0.511 | $9.11 \times 10^{-6}$ | Decrease |
| FOG | −0.156 mg/L/y | 0.123 | 0.0576 | No significant trend |
| Phenol | +0.00187 mg/L/y | 0.545 | $3.20 \times 10^{-6}$ | Increase |
| MBAS | −0.0635 mg/L/y | 0.091 | 0.1053 | No significant trend |
| $NO_3$-N | +1.483 mg/L/y | 0.319 | 0.00115 | Increase |
| T-N | −5.089 mg/L/y | 0.204 | 0.0121 | Decrease |
| $PO_4$-P | −1.726 mg/L/y | 0.394 | 0.000205 | Decrease |
| Cl | −11.675 mg/L/y | 0.658 | $5.41 \times 10^{-8}$ | Decrease |
| $HCO_3$ | −1.022 mg/L/y | 0.001 | 0.8993 | No significant trend |
| SAR | −0.117 units/y | 0.456 | $4.21 \times 10^{-5}$ | Decrease |
| *E. coli* ($log_{10}$) | −0.0923 $log_{10}$/y | 0.130 | 0.0508 | Marginal decrease |

Note: Slopes are from ordinary least-squares regression against decimal year using all 30 campaign observations. *E. coli* was analyzed on the $log_{10}$ scale; all other parameters were analyzed on their measured scales. p-values are two-sided and presented as exploratory nominal values.

Table 9: Factor analysis scores following varimax rotation for final-effluent quality parameters at Karak DWWTP, 2016–2025

| Parameter | PC1 | PC2 | PC3 | PC4 |
|---|---|---|---|---|
| pH | -0.29 | **0.75** | -0.09 | 0.47 |
| DO | -0.30 | 0.04 | 0.17 | **0.89** |
| BOD5 | **0.71** | 0.35 | 0.20 | 0.38 |
| COD | **0.85** | 0.40 | -0.03 | 0.40 |
| TDS | **0.92** | 0.25 | -0.27 | -0.25 |
| TSS | **0.80** | 0.39 | -0.05 | 0.18 |
| FOG | 0.41 | **0.75** | -0.14 | 0.19 |
| Phenol | -0.27 | -0.29 | **0.88** | 0.29 |
| MBAS | 0.49 | -0.04 | **0.84** | -0.19 |
| NO3-N | -0.41 | 0.23 | **0.65** | 0.35 |
| T-N | 0.42 | **0.87** | 0.08 | -0.04 |
| PO4-P | **0.90** | 0.19 | 0.28 | -0.29 |
| Cl | **0.95** | 0.04 | 0.18 | -0.08 |
| HCO3 | 0.49 | 0.17 | **0.79** | -0.38 |
| SAR | **0.93** | 0.05 | -0.09 | -0.09 |
| *E. coli* | 0.39 | 0.39 | -0.24 | **0.67** |
| Eigen value | 8.35 | 4.41 | 3.59 | 2.75 |
| Total variance (%) | **46.25** | **15.79** | **15.25** | **12.25** |
| Cumulative variance (%) | 46.25 | 62.04 | 77.29 | 89.54 |
| Possible source/driver | Residual organic–solids–salinity–phosphorus effluent matrix | Nitrogen–FOG–pH operational factor | Phenolic– surfactant/nitrification–alkalinity factor | Oxygenation–microbial effluent-quality factor |

*Hierarchical clustering of wastewater quality patterns*

HCA grouped the final-effluent variables into four clusters (Fig. 1). Cluster 1 comprised $BOD_5$, COD, TSS, TDS, Cl, SAR and $PO_4$-P, showing a residual organic/solids/salinity covariance grouping. This broadly resembles PC1 but is not independent validation because both analyses use the same 30 × 16 standardized datasets. HCA provides valuable linkage information by identifying variables that agglomerate at shorter distances, thereby serving as a complementary descriptive perspective on the underlying correlation structure. Cluster 2 comprised pH, FOG and T-N (Fig. 1). This grouping is reported as an association among these variables in the final effluent. While associations with nitrogen transformation, grease dynamics, pH/alkalinity balance, or aeration remain mechanistically sound, they cannot be validated in the absence of paired process and influent data; consequently, Cluster 2 is construed strictly as a co-variation pattern rather than proof of a distinct treatment mechanism. Cluster 3 grouped phenol, MBAS, $NO_3$-N and $HCO_3$ (Fig. 1). The cluster may be consistent with a mixed trace-organic/nutrient/alkalinity pattern, but neither a detergent source nor a specific nitrification mechanism is established by the clustering. The grouping is used only to describe co-variation in the monitored final effluent. Cluster 4 comprised DO and *E. coli* (Fig. 1). Their proximity indicates co-variation within the dataset, not a demonstrated causal link between oxygenation and microbial removal or disinfection. Because no disinfection, hydraulic or process-operating data were available, the cluster is described as a DO–microbiological quality association requiring independent confirmation. Overall, HCA showed four covariance groupings broadly consistent with the PCA structure. While this consistency substantiates a coherent descriptive pattern within the dataset, it does not provide independent validation, identify specific pollution sources, or confirm underlying treatment mechanisms.

*PMF based source apportionment*

The four-factor PMF solution comprised one dominant and three lower-average statistical profiles (Fig. 2); Factor 1, 54.0%; Factor 2, 20.3%; Factor 3, 16.7%; and Factor 4, 9.1%. These percentages characterize the mean apportioned matrix derived from the PMF model and should not be construed as the proportional contributions of verified external pollutant sources. Environmental interpretation is based on the variables with the largest relative contributions within each profile, and the labels are descriptive hypotheses that require independent influent, source or operational data for validation. Lower-average factors may still be important when they dominate regulatory-critical variables such as FOG, *E. coli*, phenol or MBAS. Factor 1 (54.0%) was characterized by Cl (86.0%), TDS (80.5%), $HCO_3$ (80.1%), SAR (79.1%), COD (78.0%), TSS (68.5%) and $BOD_5$ (61.7%) (Fig. 3). This profile is therefore described as a mineralized–organic residual pattern, reflecting co-apportionment of salinity/alkalinity indicators with residual organic/solids variables. It is not treated as a single confirmed pollutant source. Although the profile aligns with persistent final-effluent matrix neither source origin nor underlying treatment mechanism can be definitively resolved from effluent monitoring data in isolation. Factor 2 (20.3%) was characterized by $PO_4$-P (77.0%), $NO_3$-N (75.5%), T-N (70.1%) and pH (67.0%) (Fig. 3). It is therefore described as a nutrient–pH statistical pattern. Although nitrogen transformation and alkalinity dynamics serve as plausible process interpretations, the profile fails to confirm a specific nitrification, denitrification or polishing mechanism due to the absence of corresponding process measurements.

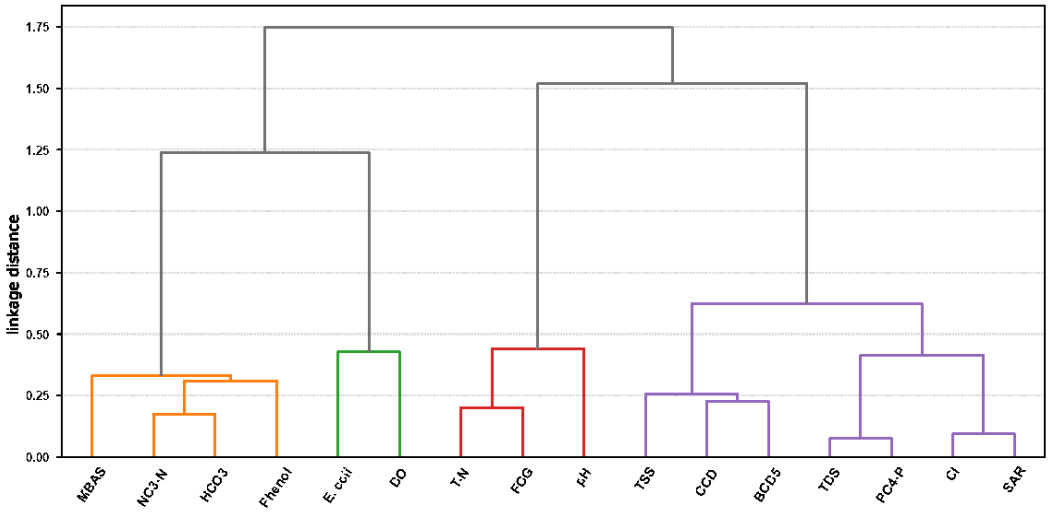


Fig. 1: Hierarchical cluster analysis dendrogram of final effluent-quality parameters from Karak DWWTP during 2016–2025

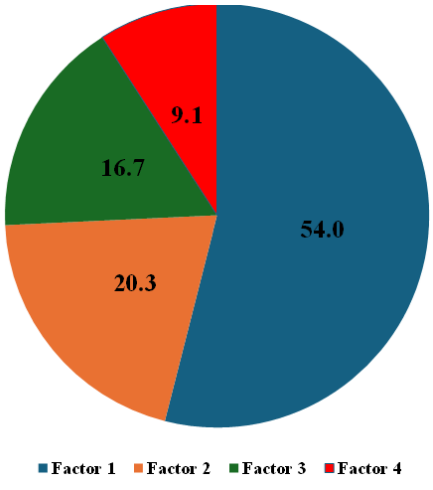


Fig. 2: Average contributions of PMF factors

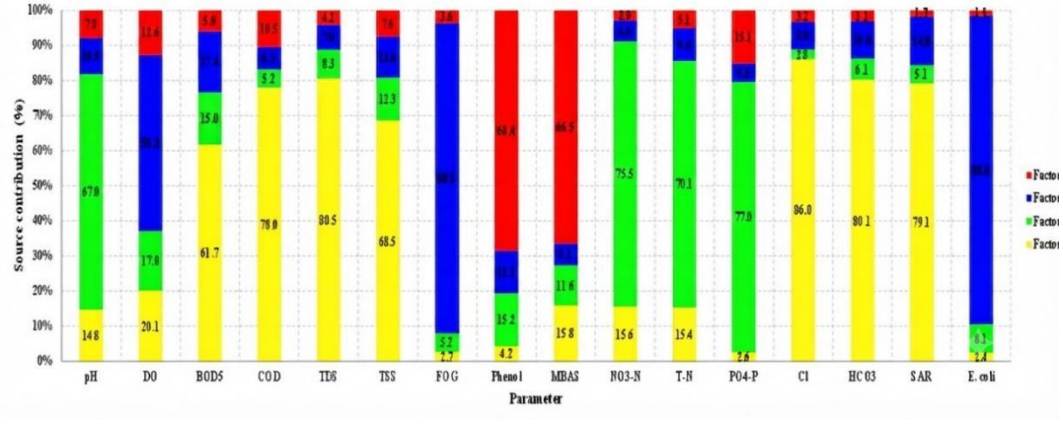


Fig. 3: Relative contributions of studied variables to PMF factors

Factor 3 (16.7%) was characterized most strongly by FOG (88.5%) and *E. coli* (88.0%), with a substantial DO contribution (50.3%) (Fig. 3). This is described as a FOG–microbiological–DO association. Owing to a constrained sampling frequency of three annual campaigns and the absence of flow or operational records, this profile cannot be construed as evidence of episodic, short-term operational or hydraulic events, nor does it substantiate a specific carryover mechanism. Although this factor holds environmental significance by dominating two compliance-sensitive indicators, the co-apportionment results do not confirm that FOG induced microbial carryover, nor do they establish that shifts in aeration/disinfection generated the observed pattern. Factor 4 (9.1%) was characterized by phenol (68.4%) and MBAS (66.5%) (Fig. 3). It is therefore described as a phenol–MBAS trace-organic/surfactant statistical pattern. MBAS is an anionic-surfactant indicator, but phenol is not source-specific; consequently, the factor cannot be assigned confidently to domestic detergents, cleaning agents or a particular external source from the present data. Achieving definitive source attribution necessitates targeted influent and source characterization efforts. Collectively, the PMF profiles delineate dominant, matrix-wide co-apportionment patterns from lower-average profiles that exert a disproportionate influence on specific sensitive variables. This is useful for prioritizing follow-up monitoring, but it does not convert statistical factors into confirmed sources. Accordingly, numerical PMF stability is considered separately from statistical factor structure and from environmental/process hypotheses, which require independent validation.

*Implications for wastewater reuse and environmental management strategies*

Management implications are based first on direct JS 893:2021 exceedances and only secondarily on the statistical patterns. The most defensible priorities are improved control of residual organics/solids, nutrients, FOG, phenol/MBAS and *E. coli*, together with management of bicarbonate and chloride where relevant to the intended reuse. Priority should therefore be given to sustained compliance with individual critical parameters rather than reliance on composite indices or statistical factor scores alone. Routine monitoring should also be strengthened to identify persistent exceedances and support timely corrective management. Because comprehensive operational data regarding aeration configuration, sludge age, secondary clarification, disinfection, FOG removal, nutrient-removal setups, influent compositions, and energy/economic requirements were unavailable, the findings cannot justify recommending specific unit-process upgrades, such as tertiary filtration, anoxic/anaerobic zones, ultraviolet (UV) irradiation, ozonation, or advanced desalination. Such options necessitate rigorous, site-specific engineering assessments prior to selection or deployment. Furthermore, the reintroduction of restricted irrigation should only be entertained once sustained, category-specific compliance is verified through higher-frequency monitoring, with a particular emphasis on microbiological and other critical parameters.

*Study limitations*

This study has several limitations that directly constrain interpretation. The dataset contains 30 campaign-level observations for 16 variables, with only three campaigns per year; therefore, PCA, HCA and PMF are exploratory and cannot resolve seasonal or short-term operational events. Although the 2018 conversion from trickling filters to activated sludge falls within the monitoring period, limited pre-upgrade observations and a lack of paired operational data preclude definitive causal attribution between the pre- and post-conversion phases. Only final effluent was

analyzed; no influent, process-unit, hydraulic, rainfall, sludge, disinfection or source-profile data were available, so multivariate components and PMF factors represent statistical associations or potential process-associated patterns rather than confirmed sources or mechanisms. Furthermore, the monitoring protocol encompassed a restricted suite of contaminants, omitting pharmaceuticals, emerging pollutants, heavy metals, comprehensive pathogen indicators or antibiotic resistance markers. WQI and WPI are screening tools whose results depend on parameter selection, reference standards and aggregation; they do not replace direct compliance with critical regulatory limits. These constraints are now explicitly integrated into the formulation of management implications, emphasizing that subsequent investigations should couple high-frequency surveillance with comprehensive influent characterization and detailed process-operational records. The linear trend analysis evaluates monotonic change over the complete 2016–2025 record; it does not resolve seasonal cycles and cannot isolate the effect of the 2018 treatment conversion from other unmeasured temporal changes.

## CONCLUSION

This study provides an integrated assessment of long-term final-effluent quality and reuse suitability at Karak DWWTP during 2016–2025. Direct comparison against JS 893:2021 standards revealed that the effluent remained limited in its suitability for multiple intended applications, constrained predominantly by residual organic matter, suspended solids, nutrients, bicarbonate, phenol, FOG, and *E. coli*. The observed exceedances indicate that reuse suitability varied substantially among intended applications and that compliance with individual critical parameters remains more informative than a single aggregated measure of water quality. WQI and WPI were useful as supplementary screening tools, but the additional parameter-contribution and sensitivity analyses demonstrated that their magnitudes can be strongly controlled by a small number of variables and by category-specific standards. *E. coli* overwhelmingly dominated the most restrictive Class D irrigation and groundwater-recharge indices, whereas phenol exerted the greatest WQI influence in Classes B and C. This contrast demonstrates that high composite-index values may arise from different controlling parameters depending on the intended reuse category, thereby requiring parameter-specific examination before management decisions are made. Furthermore, an equal-weight sensitivity analysis further demonstrated that index classification are sensitive to variations in weighting architectures, emphasizing the necessity of interpreting composite indices in conjunction with direct, parameter-specific compliance rather than as independent indicators of treatment efficacy or health risk. Accordingly, composite indices are best regarded as screening and prioritization tools that complement, rather than replace, regulatory assessment of critical microbiological, chemical, and physicochemical parameters. The 2016–2025 linear trend analysis provided an additional temporal perspective. Significant declines in BOD5, COD, TDS, TSS, T-N, PO4-P, chloride, and SAR indicate improvement in several organic, solids, nutrient, and salinity-related indicators, while significant increases in DO, phenol, and NO3-N show that improvement was not uniform across all parameters. These trends outline directional shifts within the monitored effluent; however, they cannot be construed as indicators of specific treatment mechanisms due to the absence of corresponding influent, hydraulic, operational, and process-unit records. PCA, HCA, and PMF similarly identified coherent covariance, similarity, and factor-profile structures, but these

statistical patterns do not independently establish causal sources or treatment pathways. Overall, direct JS 893:2021 compliance remains the primary basis for reuse decisions. Given the parameters of the monitored conditions, practices such as unrestricted irrigation, environmentally sensitive surface-water discharge, and artificial groundwater recharge are scientifically unwarranted. Such applications should be considered only after sustained category-specific compliance, higher-frequency monitoring, and verification of critical parameters. Future assessments should combine higher-frequency monitoring with influent, operational, hydraulic, process-unit, and source-specific measurements so that temporal changes, treatment performance, source attribution, and required process interventions can be evaluated with greater confidence and stronger engineering and management relevance for sustainable wastewater reuse and environmental protection.

## AUTHOR CONTRIBUTIONS

E.R. Tarawneh was solely responsible for the conceptualization and design of the study, data collection, data analysis and interpretation, and preparation and revision of the manuscript and final approval of the submitted version.

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## CONFLICT OF INTEREST

The author declares that there is no conflict of interest regarding the publication of this manuscript. In addition, ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy have been completely observed by the authors.

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## POSITIVE AI STATEMENT

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## ABBREVIATIONS

| | |
|---|---|
| *%* | Percent |
| *°C* | Degrees Celsius |
| $log_{10}$ | Base-10 logarithm |
| $HCO_3$ | Bicarbonate |
| $BOD_5$ | Biochemical oxygen demand |
| *BS-DISP* | Bootstrap–displacement |
| *COD* | Chemical oxygen demand |

| | |
|---|---|
| *Cl* | Chloride |
| $R^2$ | Coefficient of determination |
| *CV* | Coefficient of variation |
| $m^3$ | Cubic meters |
| $m^3/d$ | Cubic meters per day |
| $m^3/y$ | Cubic meters per year |
| *DISP* | Displacement |
| *DO* | Dissolved oxygen |
| *DWWTP* | Domestic wastewater treatment plant |
| *E. coli* | Escherichia coli |
| *G* | Factor contribution |
| *F* | Factor profile |
| *FOG* | Fats, oils, and grease |
| *Q1* | First quartile |
| *ha* | Hectare |
| *HCA* | Hierarchical cluster analysis |
| *IBM* | International Business Machines |
| *IPN* | Intestinal pathogenic nematode eggs |
| *KMO* | Kaiser-Meyer-Olkin |
| *km* | Kilometers |
| *LDO* | Luminescence measurement of dissolved oxygen |
| *Q2* | Median |
| *MDL* | Method detection limit |
| *MBAS* | Methylene blue active substance |
| *mg/L* | Milligram per liter |
| *MCM* | Million cubic meters |
| *MPN* | Most probable number |
| $NO_3$–*N* | Nitrate-nitrogen |
| $PO_4$–*P* | Phosphate -phosphorus |
| *PLi* | Pollution load |
| *PMF* | Positive matrix factorization |
| *PCA* | Principal component analysis |
| *QA* | Quality assurance |
| *QC* | Quality control |
| *RSD* | Relative standard deviation |
| *SAR* | Sodium adsorption ratio |
| *SPSS* | Statistical package for the social sciences |
| *TSS* | Suspended solids |
| *Q3* | Third quartile |
| *TDS* | Total dissolved solids |
| *T-N* | Total nitrogen |
| EPA | U.S. Environmental Protection Agency |
| *WWQI* | Wastewater quality index |
| *WRI* | Wastewater reuse index |
| *WWTP* | Wastewater treatment plant |
| *WPI* | Water pollution index |
| *WQI* | Water quality index |
| *AI* | Artificial intelligence |
| *df* | Degrees of freedom |
| *DOS* | Department of Statistics |
| *ISO/IEC* | International Organization for Standardization/International Electrotechnical Commission |
| *JS* | Jordanian Standard |
| *JSMO* | Jordan Standards and Metrology Organization |
| *MWI* | Ministry of Water and Irrigation |
| *N/A* | Not applicable |
| *PC* | Principal component |
| *pH* | Potential of hydrogen |
| *SD* | Standard deviation |
| *SU* | Standard units |
| *UV* | Ultraviolet |
| *WHO* | World Health Organization |

## REFERENCES


Abbasi, T.; Abbasi, S.A., (2012). Water quality indices Elsevier.

Abualhaija, M., (2023). Applying the quality and pollution indices for evaluating the wastewater effluent quality of Kufranja wastewater treatment plant, Jordan. Water Conserv. Manage., 7(1): 06–11 **(6 pages)**.

Ait-Mouheb, N.; Bahri, A.; Thayer, B. Ben; Benyahia, B.; Bourrié, G.; Cherki, B.; Condom, N.; Declercq, R.; Gunes, A.; Héran, M.; Kitir, N.; Molle, B.; Patureau, D.; Pollice, A.; Rapaport, A.; Renault, P.; Riahi, K.; Romagny, B.; Sari, T.; Sinfort, C.; Steyer, J.-P.; Talozi, S.; Topcuoglu, B.; Turan, M.; Wéry, N.; Yıldırım, E.; Harmand, J., (2018). The reuse of reclaimed water for irrigation around the Mediterranean Rim: a step towards a more virtuous cycle? Reg. Environ. Change., 18(3): 693–705 **(13 pages)**.

Al-hasanat, A.; Chemack, F.; Sabbahi, S.; Nouiri, I.; Karanis, P.; Ayed, L. Ben, (2025). Exploring treated wastewater reuse as an alternative option to cope with water scarcity: comparative review in Tunisia and Jordan. Water Pract. Technol., 20(12): 2881–2898 **(18 pages)**.

Al-Hazmi, H.E.; Mohammadi, A.; Hejna, A.; Majtacz, J.; Esmaeili, A.; Habibzadeh, S.; Saeb, M.R.; Badawi, M.; Lima, E.C.; Mąkinia, J., (2023). Wastewater reuse in agriculture: Prospects and challenges. Environ. Res., 236: 116711 **(26 pages)**.

Alfarra, A.; Kemp-Benedict, E.; Hötzl, H.; Sader, N.; Sonneveld, B., (2011). A framework for wastewater reuse in Jordan: utilizing a modified wastewater reuse index. Water Resour. Manage., 25(4): 1153–1167 **(15 pages)**.

Alihosseini, S.H.; Torabian, A.; Semiromi, F.B., (2020). Evaluation of treated municipal wastewater effluent for agricultural irrigation purposes using the fuzzy effluent quality index (FEQI). Water Supply. 20(1): 148–156 **(9 pages)**.

Ammary, B.Y., (2007). Wastewater reuse in Jordan: present status and future plans. Desalination, 211(1–3): 164–176 **(13 pages)**.

Anyango, G.W.; Bhowmick, G.D.; Bhattacharya, N.S.; Sahoo Bhattacharya, N., (2024). A critical review of irrigation water quality index and water quality management practices in micro-irrigation for efficient policy making. Desalin. Water Treat., 318: 100304 **(17 pages)**.

Ayoub, M.; El-Morsy, A., (2021). Applying the wastewater quality index for assessing the effluent quality of recently upgraded meet Abo El-koum wastewater treatment plant. J. Ecol. Eng., 22(2): 128–133 **(6 pages)**.

Ayres, R.M.; Mara, D.D.; Organization, W.H., (1996). Analysis of wastewater for use in agriculture: a laboratory manual of parasitological and bacteriological techniques World Health Organization.

Baird, R.; Rice, E.; Eaton, A., (2017). Standard methods for the examination of water and wastewaters, Water Environment Federation, Chair Eugene W. Rice, American Public Health Association Andrew D. Eaton, American Water Works Association.

Bessedik, M.; Abdelbaki, C.; Badr, N.; Tiar, S.M.; Megnounif, A., (2021). Application of water quality indices for assessment of influent and effluent wastewater from wastewater treatment plant of Oran City, Algeria. Desalin. Water Treat., 236: 306–317 **(12 pages)**.

Breulmann, M.; Müller, R.A.; Al-Subeh, A.; Subah, A.; Afferden, M. van, (2019). Reuse of treated wastewater and biosolids in Jordan: Nationwide evaluation. Helmholtz Centre for Environmental Research – UFZ, with support from the Ministry of Water and Irrigation.

Brown, R.M.; Mccleiland, N.J.; Deiniger, R.A.; O'Connor, M.F., (1972). Water quality index–crossing the physical barrier (Jenkis, SH ed) Proceeding.

Brown, S.G.; Eberly, S.; Paatero, P.; Norris, G.A., (2015). Methods for estimating uncertainty in PMF solutions: Examples with ambient air and water quality data and guidance on reporting PMF results. Sci. Total Environ., 518–519: 626–635 **(10 pages)**.

Chidiac, S.; Najjar, P. El; Ouaini, N.; Rayess, Y. El; Azzi, D. El, (2023). A comprehensive review of water quality indices (WQIs): history, models, attempts and perspectives. Rev. Environ. Sci. Bio. Technol., 22(2): 349–395 **(47 pages)**.

Dharmadhikari, S.; Jain, A.; Pawar, N.; Chaudhari, P.K., (2023). Direct reuse of wastewater: problem, challenge, and future direction, in: Antimicrobial resistance in wastewater and human health. Elsevier.

DOS, (2026). Population estimates at the end of 2025. Amman: Department of Statistics.

Fardous, A.-N.; Al-Hadidi, L., (2007). Waste water management and reuse in Jordan: Water resources in the Middle East: Israel-Palestinian water issues—from conflict to cooperation. springer.

Gisi, S. De; Casella, P.; Cellamare, C.M.; Ferraris, M.; Petta, L.; Notarnicola, M., (2017). Wastewater reuse. Encycl. Sustain. Technol., 4(2008): 53–68 **(16 pages)**.

Gupta, S.S.K.; Gupta, S.S.K., (2021). A critical review on water quality index tool: Genesis, evolution and future directions. Ecol. Inform., 63: 101299 **(13 pages)**.

HACH, (2006). Hach Method 10360: Luminescence Measurement of Dissolved Oxygen (LDO®) in Water and Wastewater.

Hossain, M.; Patra, P.K., (2020). Water pollution index–A new integrated approach to rank water quality. Ecol. Indic., 117: 106668 **(9 pages)**.

Jamshidzadeh, Z.; Tavangari Barzi, M., (2020). Wastewater quality index (WWQI) as an assessment tool of treated wastewater quality for agriculture: a case of North Wastewater Treatment Plant effluent of Isfahan. Environ. Sci. Pollut. Res., 27(7): 7366–7378 **(13 pages)**.

JSMO, (2021). Jordan standards and metrology organization (JSMO): standard specification "water—reclaimed domestic wastewater". JS 893:2021, 4th ed.

Kachroud, M.; Trolard, F.; Kefi, M.; Jebari, S.; Bourrié, G., (2019). Water quality indices: challenges and application limits in literature. Water, 11(2): 361 **(26 pages)**.

Kalavrouziotis, I.K.; Kyritsis, S.S.; Koukoulakis, P.H., (2023). Benefits from reclaimed wastewater and biosolid reuse in agriculture and in the environment, in: Water Management and Circular Economy. Elsevier, 273–302 **(30 pages).**

Kumari, M.; Tripathi, B.D., (2014). Source apportionment of wastewater pollutants using multivariate analyses. Bull. Environ. Contam. Toxicol., 93(1): 19–24 **(6 pages)**.

Manna, A.; Biswas, D., (2023). Assessment of drinking water quality using water quality index: a review. Water Conserv. Sci. Eng., 8(1): 6 **(18 pages)**.

Moeinzadeh, H.; Yong, K.-T.; Withana, A., (2024). A critical analysis of parameter choices in water quality assessment. Water Res., 258: 121777 **(10 pages)**.

Moghaddam, V.K.; Changani, F.; Mohammadi, A.; Hadei, M.; Ashabi, R.; Majd, L.E.; Mahvi, A.H., (2017). Sustainable development of water resources based on wastewater reuse and upgrading of treatment plants: a review in the Middle East. Desalin. Water Treat., 65: 463–473 **(11 pages)**.

MWI, (2023). Wastewater in Jordan. Amman: Ministry of Water and Irrigation.

MWI, (2024). National water strategy 2023–2040. Amman: Ministry of Water and Irrigation.

MWI, (2025a). Jordan water sector: facts and figures 2025. Amman: Ministry of Water and Irrigation.

MWI, (2025b). Water budget 2025. Amman: Ministry of Water and Irrigation. Directorate of Policies and Strategic Planning.

Nayak, B.; Panda, P.K., (2026). A comprehensive review of water quality analysis. Int. J. Image Graph., 26(04): 2650033 **(15 pages)**.

Norris, G.; Duvall, R.; Brown, S.; Bai, S., (2014). EPA positive matrix factorization (PMF) 5.0 fundamentals and user guide, US Environmental Protection Agency, Washington, DC.

Ofori, S.; Puškáčová, A.; Růžičková, I.; Wanner, J., (2021). Treated wastewater reuse for irrigation: Pros and cons. Sci. Total Environ., 760: 144026 **(15 pages)**.

Paatero, P.; Tapper, U., (1994). Positive matrix factorization: A non-negative factor model with optimal utilization of error estimates of data values. Environmetrics. 5(2): 111–126 **(16 pages)**.

Pantsar-Kallio, M.; Mujunen, S.-P.; Hatzimihalis, G.; Koutoufides, P.; Minkkinen, P.; Wilkie, P.J.; Connor, M.A., (1999). Multivariate data analysis of key pollutants in sewage samples: a case study. Anal. Chim. Acta, 393(1–3): 181–191 **(11 pages)**.

Patel, P.S.; Pandya, D.M.; Shah, M., (2023). A systematic and comparative study of Water Quality Index (WQI) for groundwater quality analysis and assessment. Environ. Sci. Pollut. Res., 30(19): 54303–54323 **(21 pages)**.

Rana, R.; Ganguly, R., (2020). Water quality indices: challenges and applications—an overview. Arab. J. Geosci., 13(22): 1190 **(11 pages)**.

Rosas Baños, M.; García Salazar, E.M., (2026). Wastewater uses for agricultural production from weak and strong sustainability perspectives. Global J. Environ. Sci. Manage., 12(2): 667-686 **(20 pages).**

Singh, K.P.; Malik, A.; Mohan, D.; Sinha, S.; Singh, V.K., (2005). Chemometric data analysis of pollutants in wastewater: A case study. Anal. Chim. Acta, 532(1): 15–25 **(11 pages)**.

Syeed, M.M.M.; Hossain, M.S.; Karim, M.R.; Uddin, M.F.; Hasan, M.; Khan, R.H., (2023). Surface water quality profiling using the water quality index, pollution index and statistical methods: A critical review. Environ. Sustain. Indic., 18: 100247 **(23 pages)**.

Tyagi, S.; Sharma, B.; Singh, P.; Dobhal, R., (2013). Water quality assessment in terms of water quality index. Am. J. water Resour., 1(3): 34–38 **(5 pages)**.

Ukoha-Onuoha, E.; Horsfall, I.T., (2026). The evolution of wastewater reuse for irrigation: Lessons learned and future directions. Next Sustainable. 7: 100253 **(13 pages)**.

Verlicchi, P.; Masotti, L.; Galletti, A., (2011). Wastewater polishing index: a tool for a rapid quality assessment of reclaimed wastewater. Environ. Monit. Assess., 173(1–4): 267–277 **(11 pages)**.

Yan, T.; Shen, S.-L.; Zhou, A., (2022). Indices and models of surface water quality assessment: Review and perspectives. Environ. Pollut., 308: 119611 **(19 pages)**.

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